Long-term monitoring and data analysis of the Tamar Bridge

E.J. Cross,[1] K.Y. Koo,[2] J.M.W. Brownjohn,[2] K. Worden[1]
[1] Dynamics Research Group, Department of Mechanical Engineering
University of Sheffield, Mappin Street, Sheffield, S1 3JD, U.K.
email: **e.j.cross@shef.ac.uk**

[2] Vibration Engineering Section, Department of Civil and Structural Engineering
University of Sheffield, Mappin Street, Sheffield, S1 3JD, U.K.

Abstract
A sound understanding of a structure's normal condition, including its response to normal environmental and operational variations is desirable for structural health monitoring and necessary for performance monitoring of civil structures. The current paper outlines the extensive monitoring campaign of the Tamar suspension bridge as well as analysis carried out in the attempt to understand the bridge's normal condition. Specifically the effects of temperature, traffic loading and wind speed on the structure's dynamic response are investigated. Finally, initial steps towards development of a structural health monitoring system for the Tamar Bridge are addressed.

1 Introduction

Monitoring campaigns of long span bridges are becoming more and more common [1] as the research fields of structural health monitoring (SHM) and performance monitoring grow. On the way to developing rigorous and reliable procedures for SHM and performance monitoring for civil structures, the normal response of a system to changes in its environmental and operational conditions must first be ascertained. In the past, many researchers have investigated the effect of environmental and operational loads on classical bridge structures. Most commonly, the relationships between features considered to be damage sensitive, such as modal frequencies, and environmental/operational conditions like temperature or traffic loadings have been explored.

The Vibration Engineering Section (VES) at the University of Sheffield have, over the last few years, developed various monitoring systems for the Tamar Suspension Bridge in South-West England. Modal parameters are automatically identified by data-driven stochastic subspace identification (SSI); environmental and operational conditions are monitored by a large network of sensors, and most recently, a Total Positioning System (TPS) has been installed to reliably measure the movement of the bridge deck and towers. Up to three years of dynamic, static and environmental data are now available.

The first part of this paper details the monitoring campaign of the Tamar Bridge. The second part of the paper details analyses carried out on three years' worth of collected data. Expressly, the effects of environmental and operational conditions on the dynamic response of the bridge are investigated, and their influence on the modal frequencies of the deck modelled.

1.1 History/specification

The Tamar Bridge (Figure 1) has been a vital transport link over the River Tamar carrying the A38 trunk road from Saltash in Cornwall to the city of Plymouth in Devon since its construction in 1961. The original bridge was designed as a conventional suspension bridge with symmetrical geometry, having a main span of 335 metres and side spans of 114 metres. With anchorage and approach spans, the overall length of the bridge reaches 643 metres. The towers are constructed from reinforced concrete, and have a height of 73 metres with the deck suspended at half this height. The towers sit on caisson foundations founded on rock.

The main suspension cables are 350mm in diameter, each consist of 31 locked-coil wire ropes and carry vertical locked-coil hangers at 9.1m intervals. The main cables are splayed at anchorages and anchored some 17 metres into rock. The truss is 5.5 metres deep and composed of welded hollow steel boxes. The original three-lane deck, spanning between cross trusses, was of composite construction with a 150mm deep reinforced concrete slab on five longitudinal universal beams and surfaced with 40mm of hand-laid mastic asphalt.

Figure 1: Tamar suspension bridge

1.2 Upgrade

When opened in 1961 Tamar Bridge was, for a short time, the longest suspension bridge in the UK and was also the first to be built after the end of World War II. In the late 1990's, after nearly four decades of use, it was found that the bridge would not be able to meet a new European Union directive that bridges should be capable of carrying lorries up to 40 tonnes in weight. Since restricting use by such vehicles would damage the local economy, the bridge was strengthened and widened.

After considering a number of options, the appointed consultant (Hyder) proposed replacement of the main deck with a lightweight orthotropic steel deck, with construction of temporary relief lanes cantilevered either side of the bridge truss. These lanes were originally intended to act as a supplementary diversion route while the main deck was being replaced but were finally adopted as part of the permanent solution.

Pairs of prefabricated orthotropic panels, each typically 15m long and 3m wide were welded longitudinally to form the 6m wide cantilever sections, also surfaced with hand-laid mastic asphalt. As proposed, a new light-weight orthotropic steel deck replaced the original three lane composite deck slab. Eighteen new locked-coil cables were installed and stressed to supplement the original suspension system, primarily to help carry the additional dead load of the new cantilever lanes and associated temporary works (Figure 2). The truss was strengthened by the installation of supplementary inverted U-shaped parallel elements fitted below the bottom chord and by welding additional steel plates at key locations.

In summary, approximately 2,800 tonnes of structural steel was added together with 125 tonnes of cables; however, when offset by the removal of the old main deck, the final weight of the suspended structure rose

Figure 2: Cantilever lanes added in the upgrade

by just 25 tonnes to 7,925 tonnes. The deck replacement process was completed in December 2001 and the bridge now carries about 50,000 vehicles per day.

This upgrade gave rise to interest in the bridge performance, and various sensor systems have been installed to measure parameters such as tensions on the additional stays, wind velocity and structural temperature. As the bridge displacement information is essential for assessing performance, surveys of the bridge deflection profile have been carried out periodically and a hydraulic levelling system has also been installed to monitor vertical deflections of the main span.

2 Monitoring the Tamar Bridge

Currently three monitoring systems are in place and running at the Tamar Bridge. The first is a Structural Monitoring System (SMS) installed by Fugro Structural Monitoring, which is used to monitor cable loads, structural and environmental temperatures and wind speed and profile. This system was installed during the upgrade to provide information on the performance and condition of the bridge during and after the strengthening and widening. The sensors used in the SMS include:

- anemometers to measure wind speed and profile;
- a fluid pressure-based level sensing system to measure deck vertical displacement;
- temperature sensors for the main cable, deck steelwork and air temperature;
- extensometers and resistance strain gauges to measure loads in additional cables.

An additional set of sensors was installed by the University of Sheffield (VES) in 2006 to monitor dynamic behaviour of the bridge deck and selected cables. Four stay cables are instrumented, each with a pair of accelerometers: one oriented horizontally and one in the vertical plane. As well as the eight cable accelerometers, three accelerometers are installed to measure acceleration of the deck.

Up until 2009, the Sheffield system recorded 64Hz-sampled time series in files at 10-minute intervals. The acquisition was managed using a virtual instrument (VI) written in LabVIEW. This VI extracted modal parameters from the acceleration data using covariance-driven stochastic subspace identification (SSI) [2]. After 2009, however, the covariance-driven SSI code was replaced with a data-driven SSI as the data-driven SSI was found to be more reliable for tracking the modal parameters, at least for the Tamar Bridge measurements.

The newest monitoring system introduced by VES is a total positioning system (TPS) which uses a robotic total station (RTS) for precise three dimensional displacement monitoring of the deck and towers, accurate to within 2 or 3mm. The RTS, shown in Figure 3, was installed in September 2009 on the roof of the Tamar Bridge Office which sits close to the bridge on the Plymouth side bank of the river. Fifteen reflectors (see figure 4) have been installed around the bridge including on the deck, main towers and side towers. Displacement measurements from each of the 15 reflectors are repeated every 30 minutes, with each measurement cycle taking about 10 minutes to cover all 15 reflectors.

Figure 3: RTS installed on the roof of Tamar Bridge Office

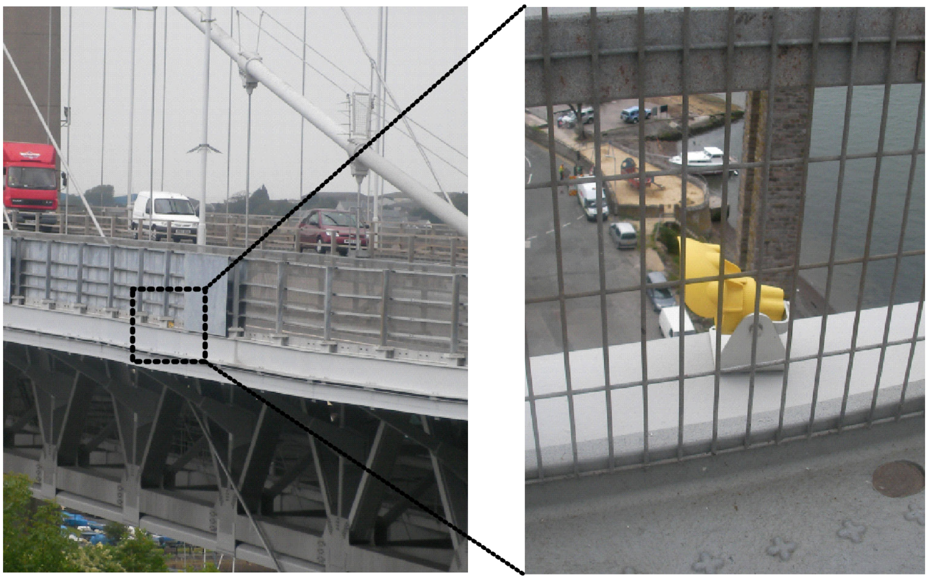


Figure 4: Reflector installed on Bridge Deck

2.1 Approach to data mining

From the three comprehensive monitoring systems described above, a huge amount of data is stored and processed daily. A Tamar Bridge SHM database has been created using the MySQL database engine to provide researchers with convenient and instant access to huge measurement sets. All the Fugro and Sheffield dynamic monitoring system data are stored and serviced in the database as well as processed modal parameters from acceleration measurements. Figure 5 shows a Tamar SHM database viewer that has been developed based on a MATLAB GUI. This viewer enables users to browse some of the important data sets (temperature, wind, traffic loadings) to find potential anomalies or understand general trends before pursuing a more detailed analysis.

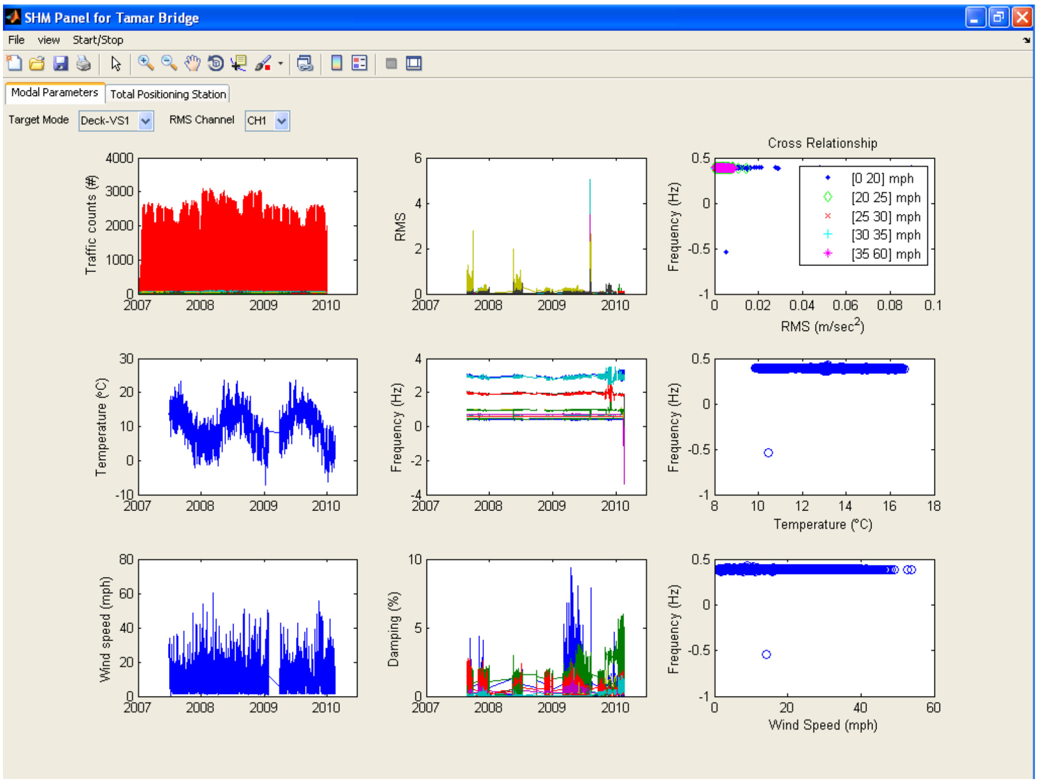


Figure 5. Tamar SHM Database viewer based on MATLAB GUI

3 Results from Tamar analysis

At least three years of reliable monitoring data is now available from the Tamar Monitoring system, which provides a most unique opportunity for development of a reliable SHM system. From this large database, the first task on the way to developing an SHM system is to understand the structure's normal condition, which is to say, how the structure responds to normal variations in environmental and operational conditions. Many researchers have sought to understand and model how varying environmental or operational conditions affect the response of a monitored structure. The dominant environmental factor affecting the dynamic response of bridge structures is generally considered to be temperature. Previous studies [3-5] have found fluctuations in modal frequency to be correlated with ambient temperature, although different mechanisms have been used to explain this. Cornwell *et al.* [4] suggested that the thermal gradient across the deck of the Alamosa canyon bridge drove the measured fluctuations in frequency. In colder climates significant shifts in frequency between above and below freezing temperatures have been attributed to an increase in stiffness explained by the Young's modulus of the asphalt on the deck at colder temperatures [5].

Besides temperature, the importance of other operational conditions has also been considered. The response of a long span bridge to high and low wind speeds was investigated in [6], where it was concluded that the modal frequencies decreased with increased response amplitude levels directly caused by increased wind speed. The effect of traffic loading has also been addressed in [7], where, for long span bridges, the influence of traffic loading on the structure's frequency was considered negligible due to the fact that the mass of a single vehicle is very small in comparison to the mass of the 'superstructure'.

For a successful SHM routine a sound understanding of all mechanisms affecting a structure's response is extremely beneficial. The monitoring of the Tamar Bridge to date has produced a large and reliable database collected over three years (including deck and cable modal frequencies, damping values, deck and tower displacements, cable tensions, traffic loadings and temperature and wind speed readings). The database is now available for analysis to support the development of an SHM strategy.

For a more complete analysis, this paper aims to study the effect of multiple environmental/operational conditions on the dynamic response of the Tamar Bridge. If the dynamic response of a structure is used for damage detection, all variations due to anything other than damage must be understood and accounted for. To this end, the effects of temperature, traffic loading, wind loading (and consequently deck acceleration) will be considered in the following analysis. The study of traffic loading here is especially rare due to the fact that many previous bridge monitoring campaigns have had to be conducted while the structure was out of action. Traffic data for the Tamar Bridge is available in the form of an hourly count of vehicle categories passing through the toll gates that service traffic going over the bridge in one direction. Webcam images are also available. From these two sources, and the vehicle weight estimates provided in a government transport statistics report [8], half hourly traffic loading estimates have been obtained.

Despite the fact that data spanning three years from the Tamar monitoring system are available, there are, understandably, periods within these three years when the monitoring system failed. One problem has been data storage; the sampling frequency of the DAQ was originally 1 Hz, which has since been changed to 0.1 Hz to overcome the problem of a lack of disc space on the storage system. In the following analysis data collected in 2007 and 2008 will be considered; this is principally because of a suspicion that the casings around one of the sensors may have become waterlogged early in 2009, which may have affected the response recording.

3.1 Dynamic response

As previously described, dynamic data for the Tamar Bridge is extracted from accelerometer data using a data-driven SSI technique (add reference to one of Ki's monitoring papers). In this section the variation of the first five modal frequencies of the deck with respect to temperature, wind speed and traffic loading are investigated. Discussion of the potentially complex effects of deck acceleration will follow in its own subsection, as it itself can be affected by traffic and wind speed.

The simplest approach in determining an environmental or operational variable's impact or importance on the fluctuations of the modal frequencies of the bridge is to plot each frequency with respect to those variables. Figure 6 shows the first five modal frequencies of the deck plotted with respect to temperature, wind speed, and traffic loading.

For further visual clarification of the influence of each variable a principal component analysis (PCA) of the frequency data is carried out. Principal component analysis takes a multivariate data set and projects it on to a new set of variables, or 'principal components,' which are linear combinations of the old variables. Of these new variables, the first principal component will account for the biggest proportion of the variance in the data set that can be described by a single axis, the second principal component will account for the second biggest proportion of the variance in the data set independent of the first, and so on. If the original number of variables is some number p, up to p new variables may be formed. Now, if the first n of these principal components represent a significant amount of the variance, it is fair to say that the data can be suitably represented solely by these n principal components without loss of any real information. Principal component analysis, therefore, works to reduce the dimensionality of the dataset, which can considerably ease analysis of datasets of high dimensionality. PCA is commonly used for a wide variety of

(a)

(b)

(c)

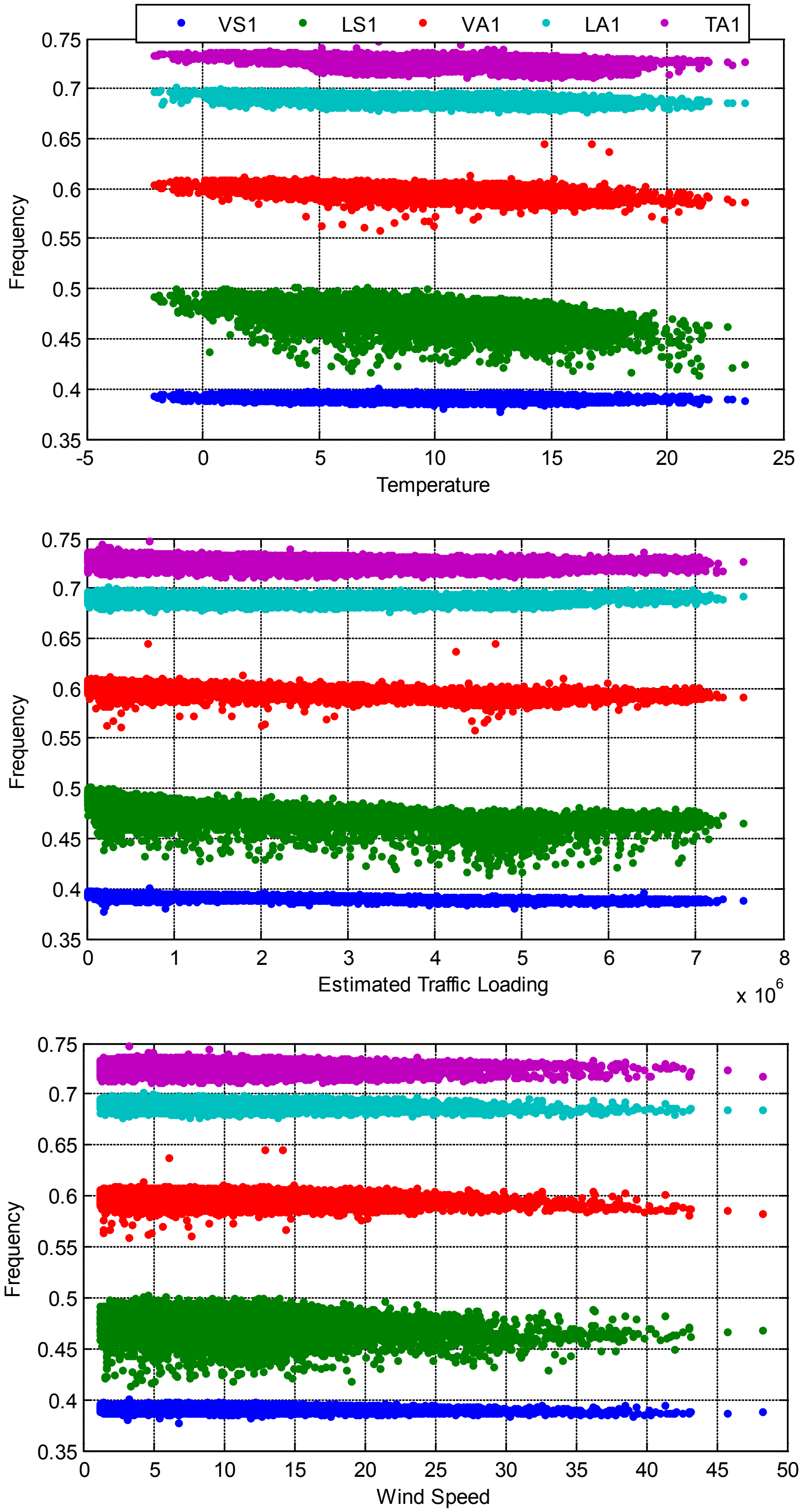


Figure 6: Deck Modal Frequencies plotted with respect to traffic loading, wind speed and temperature

(a)

(b)

(c)

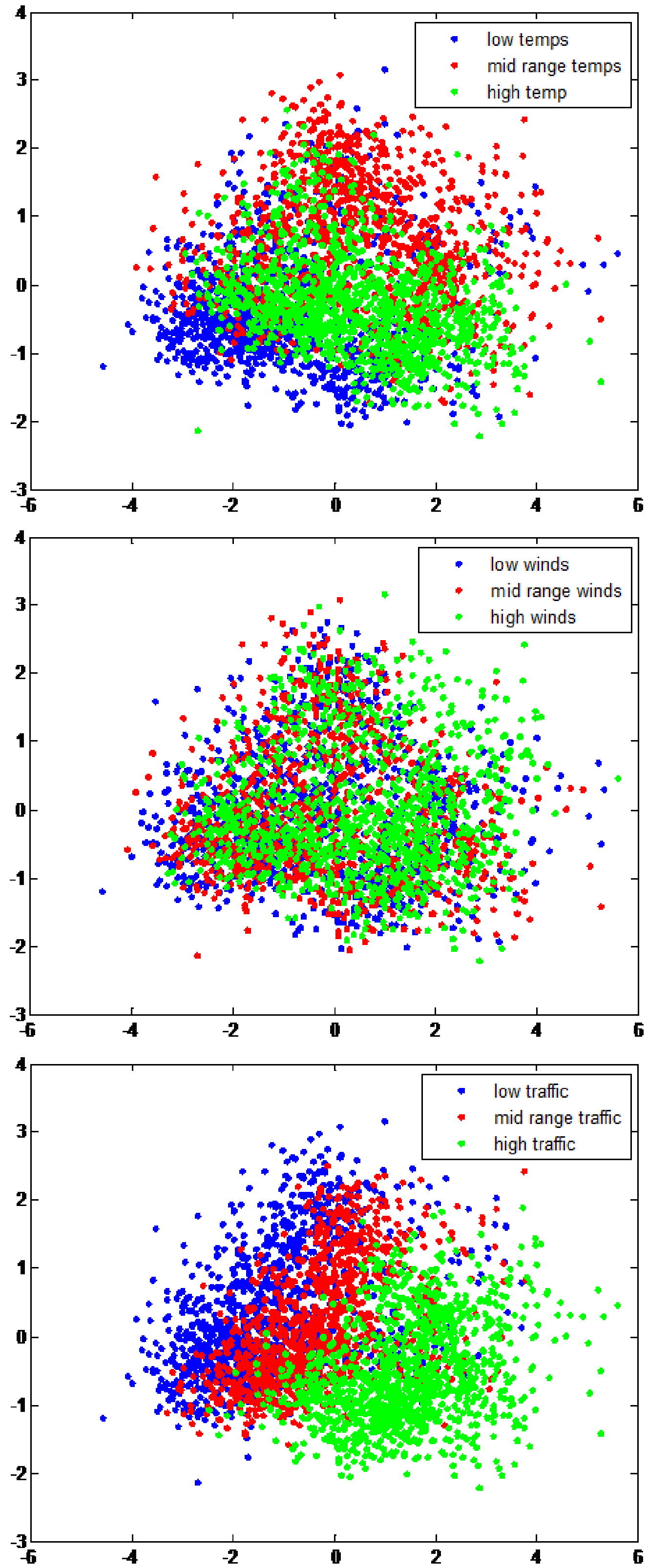


Figure 7: First two principal component scores of frequency data sorted according to temperature, wind speed and traffic loading.

tasks, here, the reduction of dimensionality of the data greatly aids visualisation of any possible structure within the data. Specifically, for the uses of this paper the first two principal components of the frequency data are plotted. Figure 7 shows the first two principal components of the data plotted against each other with each of the data points coloured according to whether they occurred at high, medium or low temperatures, wind speeds and traffic loadings. For further information on PCA readers are referred to any text book on multivariate analysis (a good example being reference [9]).

Figure 6 demonstrates that each of the first five modal frequencies of the deck have a tendency to decrease with increased temperature and increased traffic loading. For the frequency that appears most sensitive to temperature (the second, which corresponds to the first lateral symmetric mode), the frequency decreases by approximately 4.5% over a 20°C change in temperature. Similarly, the frequency for the second mode changes by around 3.5% between periods of low and high traffic. Figure 7 shows that the frequency data are uniquely distinguishable by both temperature and traffic loading. This indicates that both temperature and traffic loading have a separate but significant influence on how the frequencies vary.

The dependency of any modal frequency on wind speed is unclear from Figure 6. Although it appears that generally frequencies are lower at very high wind speeds, no clear conclusion can be drawn as the majority of the data occurs at low to moderate wind speeds. Furthermore, Figure 7 demonstrates that the frequency data cannot be sorted according to wind speed. This suggests that wind speed is not a dominant factor in determining how the frequencies vary. High wind speeds, however, have previously been found to have an influence on the dynamic characteristics of long span bridges [6], this will be taken into account later on in the analysis, when the effect of the deck acceleration is addressed.

In summary, Figures 6 and 7 indicate that temperature and traffic loading are the dominant environmental and operational factors affecting the modal frequencies of the deck. Despite the obvious mass increase that must arise from heavy traffic, previously, little attention has been given to the effect of traffic loading on modal parameters. From toll counts and web cam images, the instantaneous traffic loading on the bridge is estimated to increase by between 100 to 200 tonnes during very busy periods, which occur around 8am on weekdays. For a fixed stiffness, this change in mass would account for a 1.5-3% reduction of the modal frequencies, which is consistent with the variation encountered in Figure 6. This is in direct contrast to the conclusions drawn by Kim *et al.* [7], where traffic loads were not found to influence the modal frequencies of a long-span bridge. It should, however, be noted that the Tamar Bridge has to endure much larger traffic loads than those considered in [7].

Having determined that traffic loading should indeed be important it remains to separate out the effect of temperature from that of traffic loading. Figure 8 shows how a simple linear model with estimated traffic loading as its only input can predict the frequency change of the first mode.

The model takes the form

$$\omega_1 = 0.099 - 0.79 \times (traffic\ load). \tag{1}$$

This type of model is called a response surface model [10], the idea being originally developed by Box and Wilson [11] for modelling chemical processes. Such models are learnt from data rather than established by using the underlying physics or chemistry; they are essentially regression models of varying degrees of sophistication. Response surface models are often used to learn the input-output relations from large computer models in order to produce fast-running approximations for Monte Carlo analysis; in this context they are called meta-models, surrogate models, fast-running models or emulators. The response surfaces in the current paper will all be low-order polynomials with the parameters established using simple least-squares analysis; a general form will be given a little later.

This very simple (linear, univariate) model does a surprisingly good job and suggests that the traffic loading is a major driving force behind the frequency fluctuations of the first mode. Furthermore the model's prediction capability is not improved by adding a temperature dependent variable, even when longer time-scales are considered, where one might expect to encounter seasonal effects.

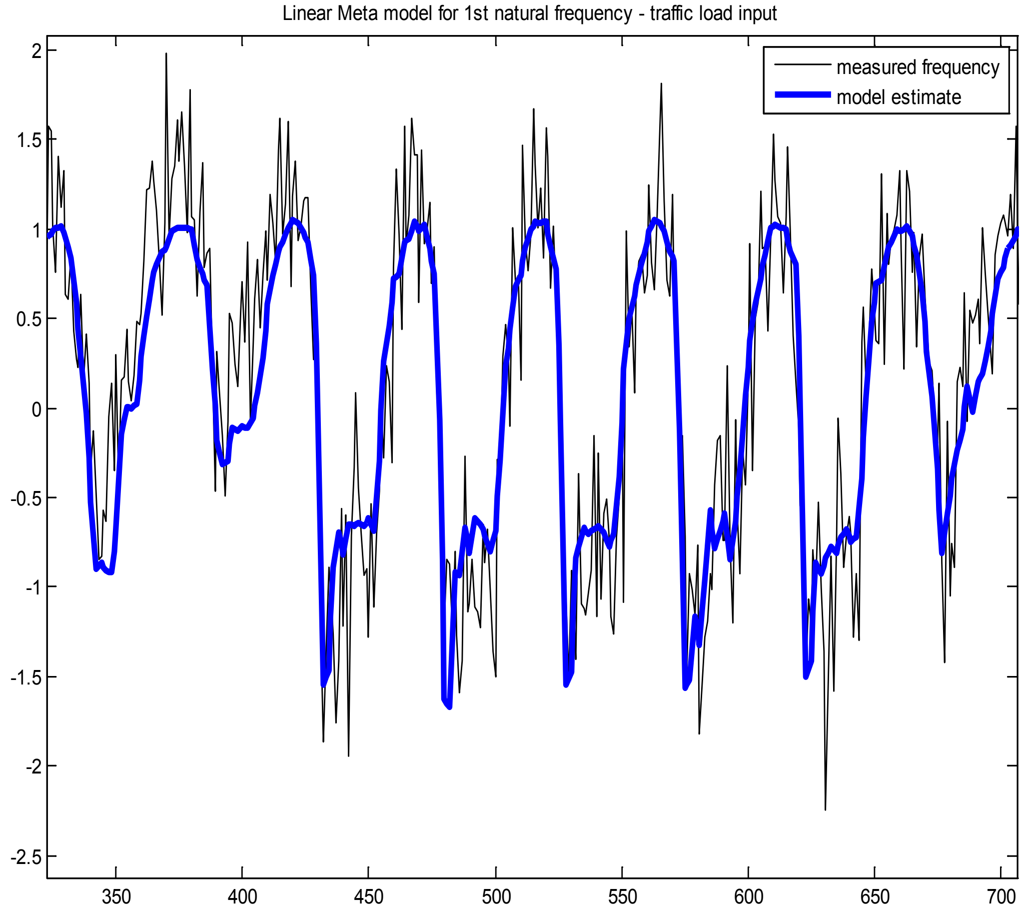


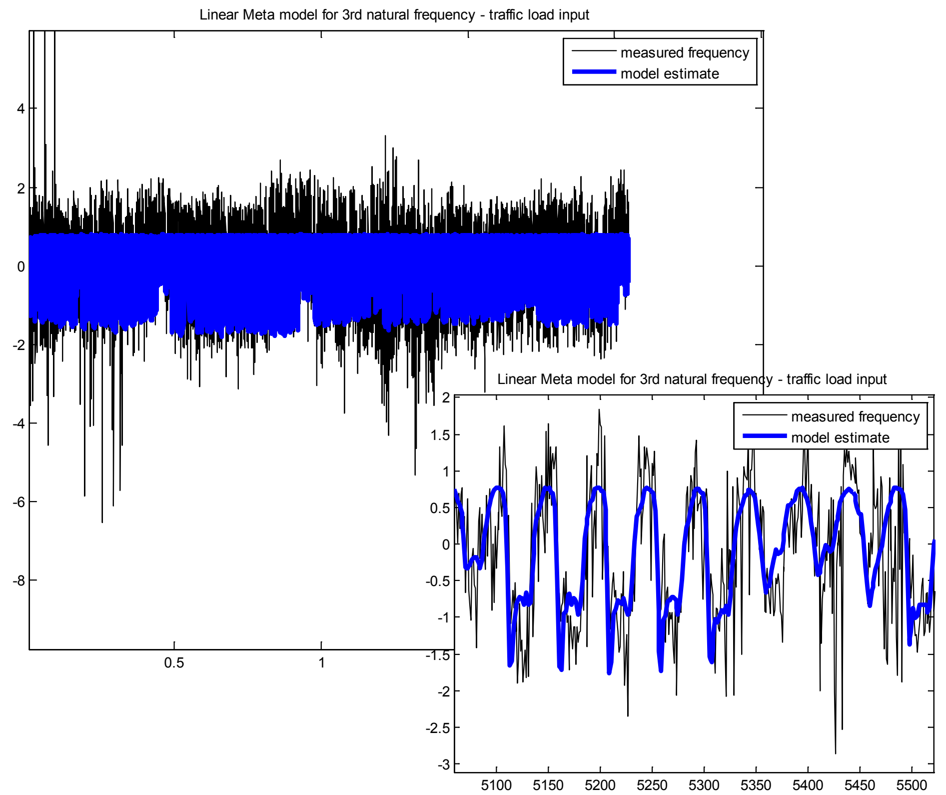
Figure 8: Linear model of first deck modal frequency with traffic loading input only.

Similarly for the next two frequencies, a linear model of the form (1) can predict the frequency change very well. However, unlike the first mode, adding a temperature dependent variable to the model does improve the prediction capability for data over a longer time period. Figure 9 demonstrates the effect of including an additional temperature dependent variable in the model of the third modal frequency. Over short time periods (as illustrated in the inset figures) the addition of a temperature variable has no visible effect, however, the general fit to all recorded data (main figures) appears to be improved, which suggests that the temperature has more of a seasonal influence than daily, for this mode at least.

It should be noted that although a simple model form including temperature and traffic loading inputs can recreate the general trend of the second mode (which is the first lateral bending mode), there are large daily drops recorded in the second modal frequency which cannot be recreated. These large drops generally occur at times of high traffic, and are rare at weekends. The current hypothesis is that these large drops are caused by short term large traffic loadings, such as would result from a traffic jam. Unfortunately the traffic loading estimates have to be interpolated from hourly traffic counts, and as such cannot predict short term traffic loads. It is expected that a more sophisticated traffic loading estimate would improve model fidelity for the second mode considerably.

Similar model fits can predict the general trends in the fluctuations of the fourth and fifth frequencies, however, the prediction errors are comparably large. A more complex model structure will be needed to accurately predict changes in the fourth and fifth modal frequencies.

(a)



(b)

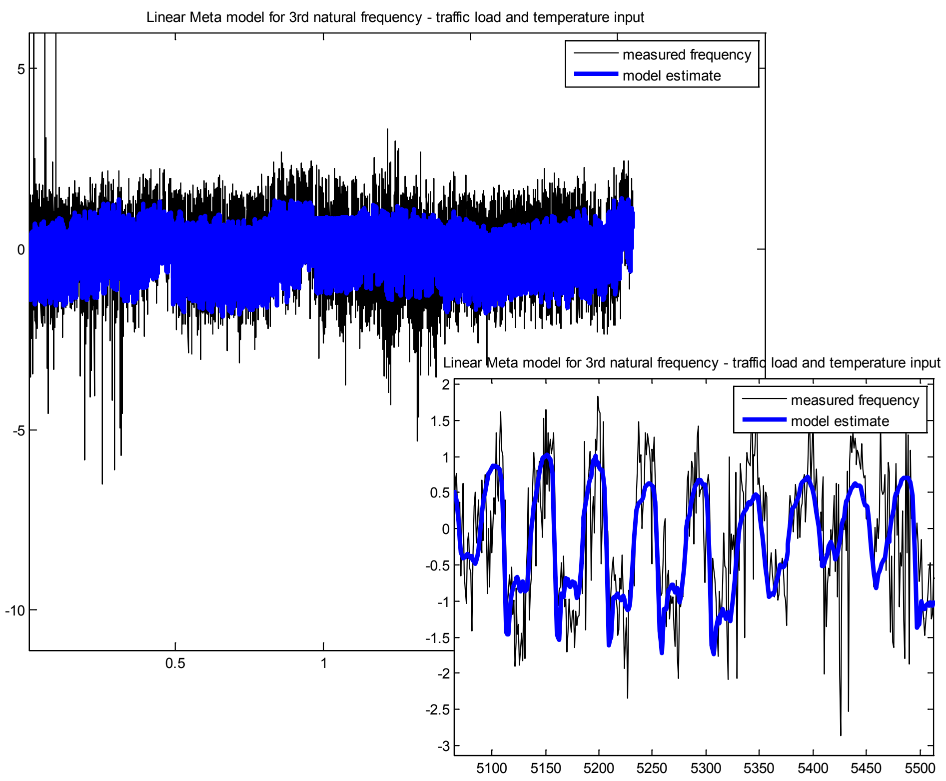


Figure 9: (a) linear model of the third deck modal frequency with traffic loading input. (b) linear model of third deck modal frequency with traffic loading and temperature inputs.

3.1.1 Deck Acceleration

Closely linked to the wind profile, and also the dynamics of traffic loading is the acceleration of the deck. Figure 10 shows the plot of the first five modal frequencies with respect to the root-mean-squared (RMS) values of vertical and horizontal deck acceleration. These plots show a clear tendency for decreased frequencies at higher amplitudes of deck acceleration, for both horizontal and vertical accelerations. This amplitude dependency indicates that the system is nonlinear, which is not unexpected for such a complex structure. This discovered nonlinearity does not in fact overly increase the complexity of the response surface analysis carried out here, it rather just increases the number of parameters that must be considered when attempting to understand, or even predict, the fluctuations in the modal frequencies. This having been said, on close inspection of Figure 10, the correlations between modal frequency and deck acceleration appear non-trivial, especially for the second modal frequency; this will require further investigation if the relationship between the two is to be well understood.

(a)

(b)

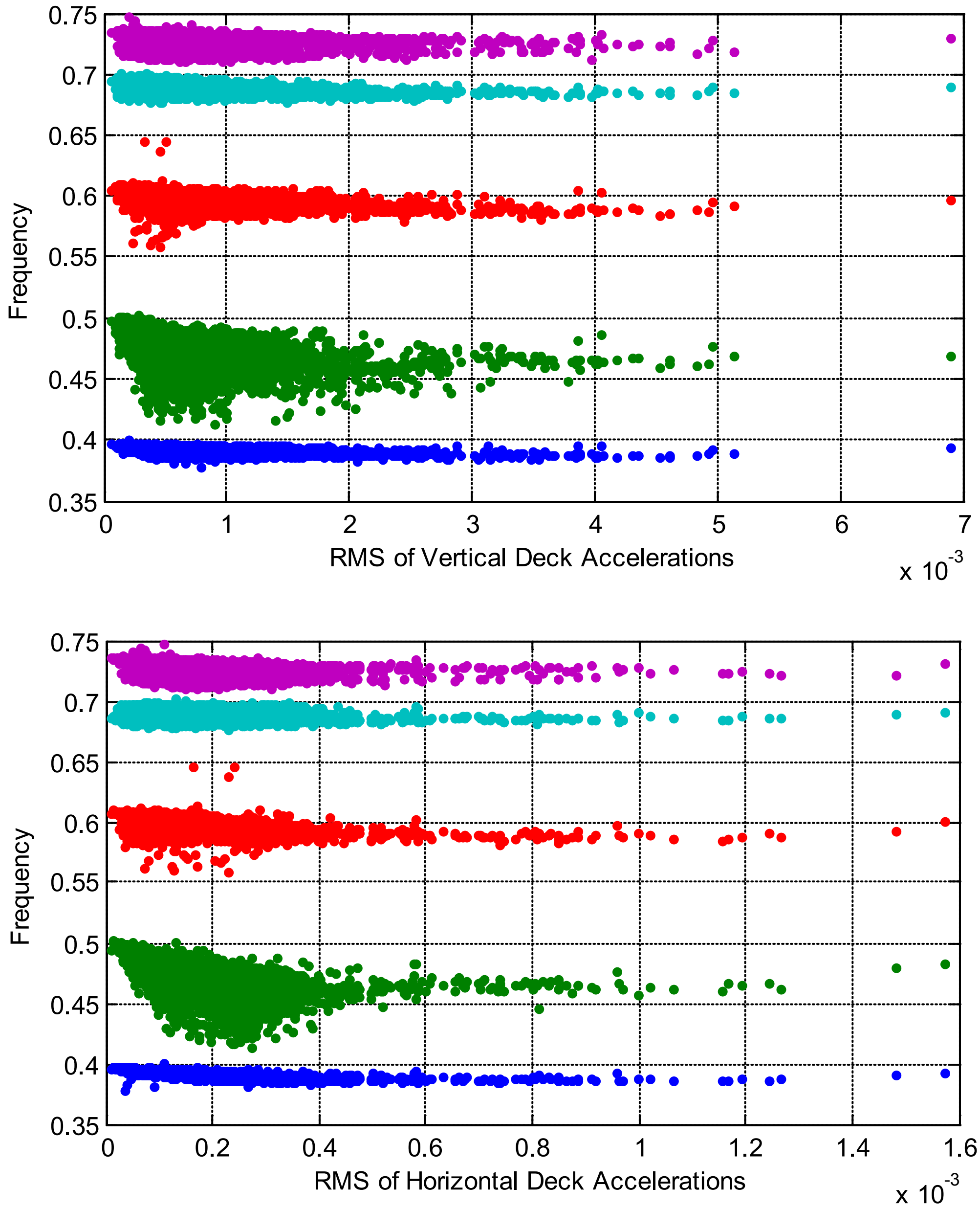
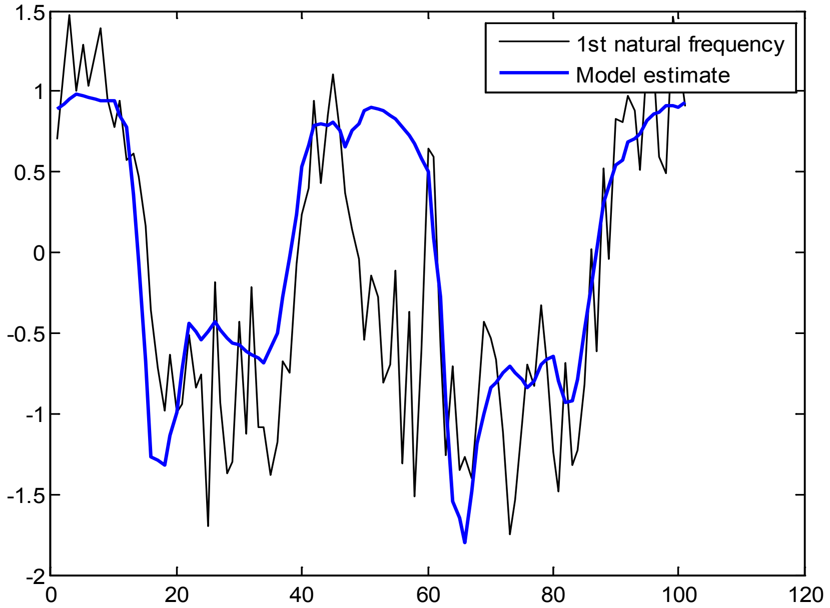


Figure 10: Modal frequency plotted according to RMS of vertical deck accelerations (above) and horizontal deck accelerations (below).

Figure 10 demonstrated that increases in the horizontal and vertical accelerations of the deck correspond to a decrease in the modal frequencies of the first five modes. Returning to the simple response surface models for predicting frequency change, the effect of adding a variable dependent on the vertical RMS deck acceleration is now investigated. Figure 11 demonstrates the improvement of the model prediction for the first frequency over a time when high wind speeds were recorded. To understand the role of the wind speed, and therefore hopefully better understand the relationship between deck acceleration and modal frequencies, the first sensible step is to study the deck accelerations themselves.



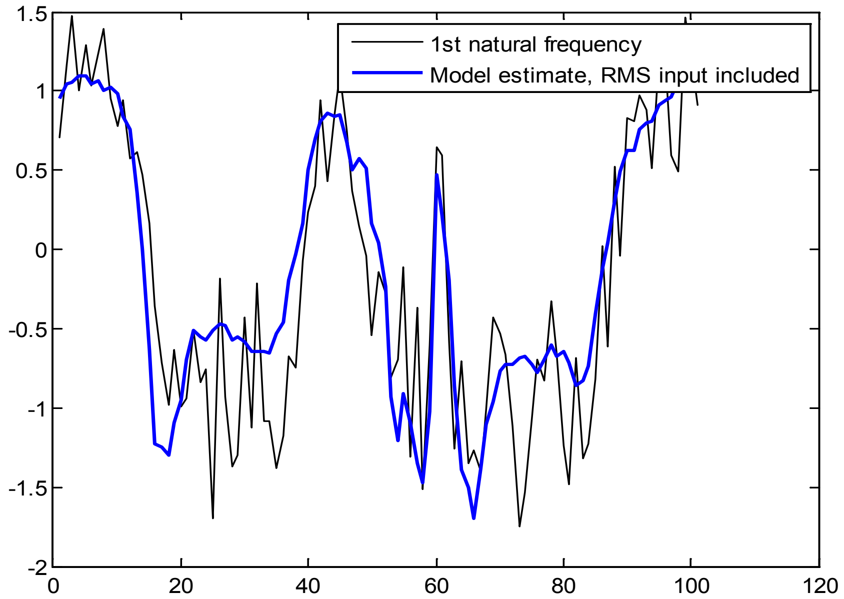


Figure 11. Above: model estimate of first modal frequency at high wind speed with traffic and temperature inputs only.

Below: model estimate of first modal frequency at high wind speed with RMS acceleration dependent variable included.

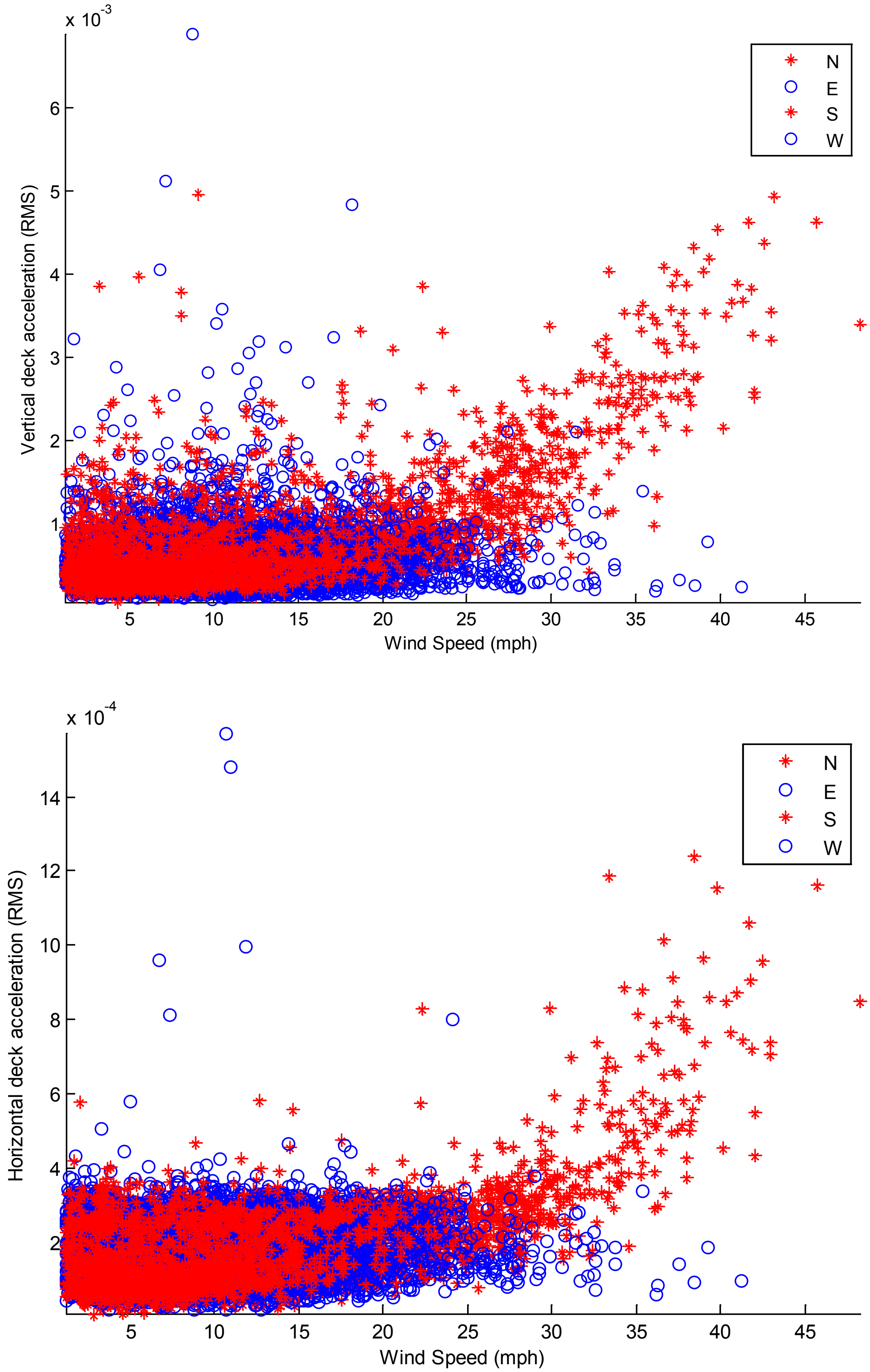


Figure 12. Vertical and horizontal deck acceleration plotted with respect to wind speed and sorted by wind direction.

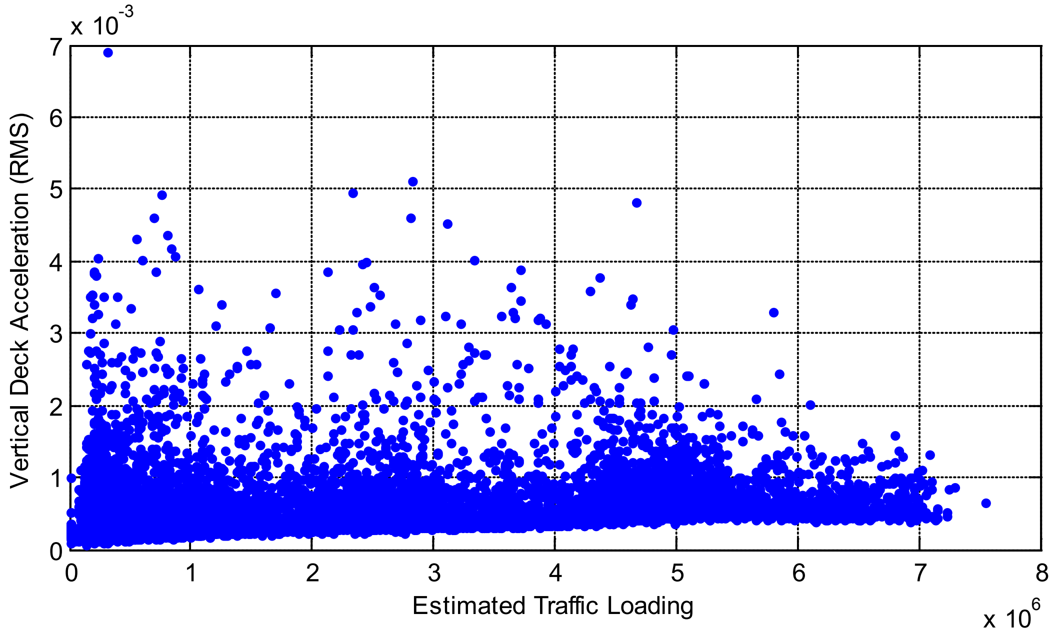


Figure 13: RMS of vertical deck acceleration plotted according to estimated traffic loading

Figure 12 is composed of plots of wind speed against vertical and horizontal deck acceleration (RMS), the plot points are also sorted according to the direction of the wind at the time. From this figure, two clear response mechanisms can be seen; when the wind is from the east or west, there is no increase in response with increased wind speed, conversely when the wind is from the north or south, above 25 mph the deck acceleration response increases (from inspection - nonlinearly) with increased wind speed. As the bridge is orientated east-west, the increasing response with increased wind speed occurs, not surprisingly, when the wind hits the bridge side on. This bi-functional relationship must be considered with any attempt to model the bridge's behaviour with respect to deck acceleration. The effect of traffic on the deck acceleration should also be considered (see Figure 13); here, the RMS of vertical and horizontal deck acceleration increases linearly with increased traffic load.

Having now a better understanding of the deck acceleration, one can return to the relationship between deck acceleration and modal frequency. Although the acceleration response of the deck acts in two different regimes according to wind direction, it does not necessarily follow that this should be reflected in the relationship between deck acceleration and modal frequency; it is possible that one regime could define the acceleration-frequency relation. Figure 14, however, shows a closer view of selected plots from Figure 10, sorted according to wind speed (and coloured according to wind direction), which clearly demonstrates a more complex relation between the two variables than perhaps expected. On inspection of Figure 14, there generally appears to be two different trends roughly separable by wind speed and direction, namely, the frequencies appear to act under a different regime when high wind speeds from a southerly direction are recorded.

3.1.2 Mathematical Models of Modal Frequencies

Based on the above analysis, more complex models to predict modal frequency change can now be contrived. Any model should include inputs based on traffic loading, temperature and also horizontal and vertical deck acceleration. Indeed, inputs based on deck acceleration should take into account the two possible response regimes discovered, which occur most likely because of differing wind patterns. Furthermore, more complex parameters can be added to reflect any nonlinearity in the response, time-lagged parameters may also be added to account for any dynamic relations between variables, which for

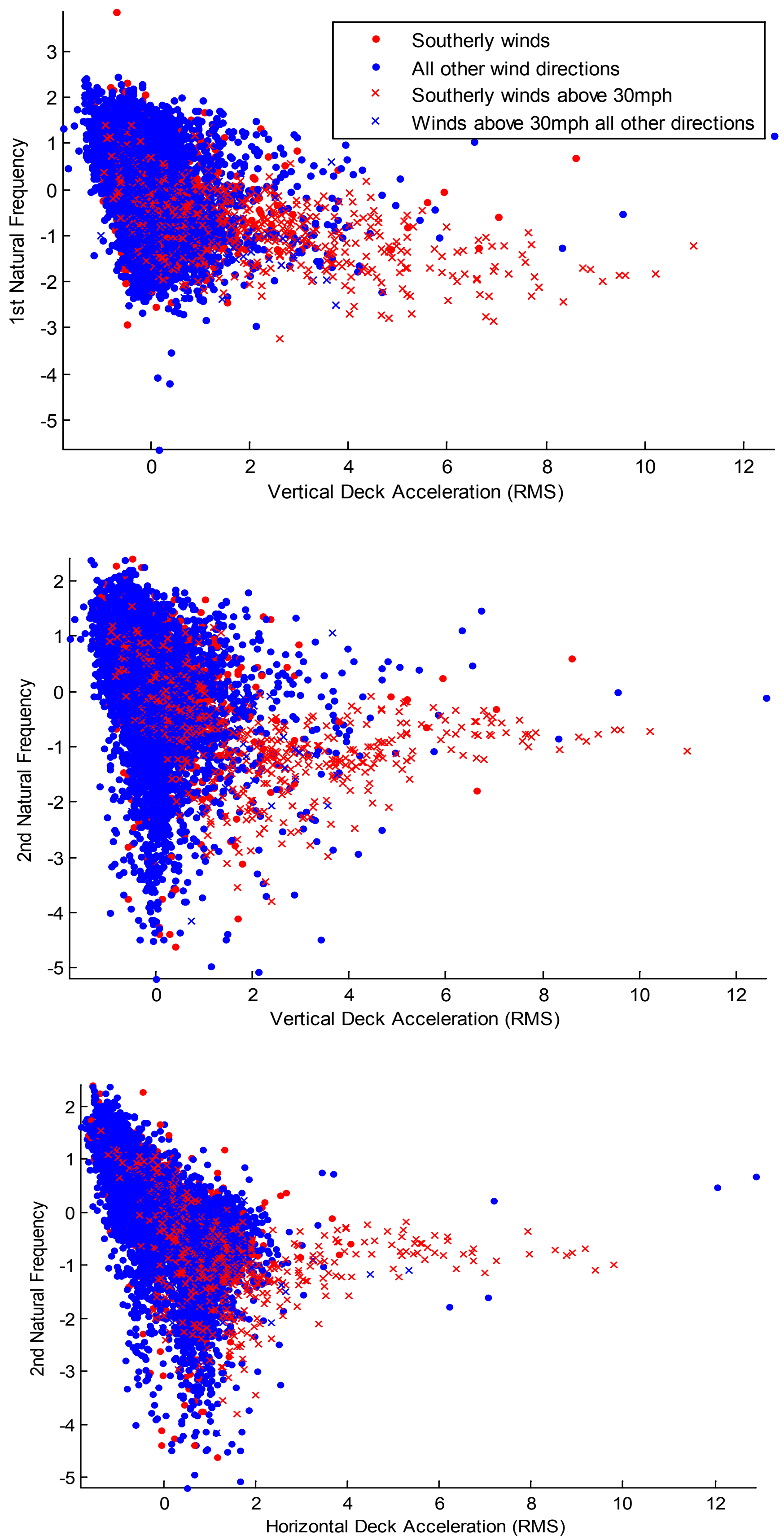


Figure 14: Variations of first and second modal frequencies plotted according to rms of deck acceleration.

example would come into play if the modal frequency at any one time depended, say, on the temperature at that same time and also the time(s) preceding it. Response surface models (see (1), for example) will be used here again. One of the main advantages of polynomial response surface models is their simplicity; they are easily fitted using least-squares methods, and they are very easy to interpret, as coefficient values can indicate the significance of a parameter (as long as input variables are normalised prior to use). Alternative approaches such as neural networks and support-vector machines have previously been explored in the literature for similar problems [12,13]. These methods are known to have powerful prediction capabilities, however, no knowledge of the physical system can be gained directly from these non-parametric approaches. Furthermore these more techniques will often require much larger quantities of training data and are much more computationally expensive.

Here, to begin, a response surface model is fitted for the first and second modal frequencies of the deck, which correspond to a symmetrical vertical mode and a symmetrical lateral mode respectively. Two feature parameters for each of the vertical and horizontal deck acceleration measurements are included; one where only acceleration values occurring when high wind speeds hitting the deck side on are recorded (zero at all other times), the other for acceleration values occurring in all other wind conditions. Quadratic terms for each of the variables are also included, along with one time-lagged term for each variable. (The time lag is 30 minutes as that is the spacing between each reading). This response surface model takes the form:

$$\omega_i = a_0 + \sum_{j=1}^{6} a_j \theta_{ij} + \sum_{j=1}^{6} b_j \theta_{(i-1)j} + \sum_{j=1}^{6} c_j \theta_{ij}^2 \tag{2}$$

Where the subscript i is indicative of time, $\{\theta_j; j = 1, \dots, 6\}$ represent the input variables described above (and listed in Table 1), and a_0, $\{a_j, b_j, c_j; j = 1, \dots, 6\}$ are constant parameters to be determined.

A problem arises when including a variable that only carries nonzero data at points where high wind speeds from the north or south were recorded, which is that these events occur relatively scarcely. This has the unfortunate implication that training must be conducted over longer periods of time to account for this.

For the first two modes, a model of form (2) was trained on 5922 data points (data collected over the period of a year). A normalised mean-squared error (MSE) will be used as a performance index for each model, which is defined here as

$$MSE = \frac{100 \sum (model\ errors)^2}{n\ (\sigma[predictions])^2} \tag{3}$$

where n is the number of data points predicted and σ denotes standard deviation. This MSE has the property that, if the mean of the data is used as the model, the MSE will be 100%. With this normalisation, values of MSE below 100% are indicative of captured correlation.

For the first mode the MSE of the model on the training data was 18.06, and when tested on data from the next year (3735 data points) was 19.9. The model of the second modal frequency could not perform as well and had a training MSE of 44.9 and a MSE of 46.2 on the test data. This was due, as explained previously, to the fact that large drops occur in the time history of the second modal frequency that the model cannot recreate, which are thought to be caused by traffic patterns. Table 1 shows the parameter/coefficient values for each input variable for each of the models. As each input variable is normalised (actually standardised to zero mean and unit variance), the model parameter can be interpreted as an importance value, the higher the value, the more influence that the term has on the modal frequency change.

	Independent/Input Variables	Parameter Mode 1	Parameter Mode 2
θ_{i5}	Horizontal Acceleration (normal wind conditions)	-0.484	-0.436
θ_{i4}	Vertical Acceleration (strong winds from North/South)	-0.352	-0.504
θ_{i1}	Traffic Loading	-0.307	-0.137
θ_{i6}	Horizontal Acceleration (strong winds from North/South)	-0.293	-0.172
$\theta_{(i-1)1}$	Traffic Loading - time lagged (t-1)	-0.198	0.177
$\theta_{(i-1)2}$	Temperature - time lagged (t-1)	-0.105	-0.292
θ_{i2}	Temperature	0.071	-0.117
${\theta_{i1}}^2$	Traffic Loading Squared	0.053	0.063
${\theta_{i4}}^2$	Squared Vertical Acceleration (strong winds from North/South)	0.048	0.088
$\theta_{(i-1)6}$	Horizontal Acceleration (strong winds from North/South) - time lagged	-0.046	0.081
${\theta_{i5}}^2$	Squared Horizontal Acceleration (normal wind conditions)	0.044	0.048
$\theta_{(i-1)3}$	Vertical Acceleration (normal wind conditions) - time lagged	-0.029	-0.047
$\theta_{(i-1)5}$	Horizontal Acceleration (normal wind conditions) - time lagged	-0.022	0.013
θ_{i3}	Vertical Acceleration (normal wind conditions)	-0.021	-0.070
$\theta_{(i-1)4}$	Vertical Acceleration (strong winds from North/South) - time lagged	-0.020	-0.138
${\theta_{i2}}^2$	Squared Temperature	0.015	-0.024
${\theta_{i6}}^2$	Squared Horizontal Acceleration (strong winds from North/South)	0.015	0.008
${\theta_{i3}}^2$	Squared Vertical Acceleration (normal wind conditions)	0.004	0.006

Table 1. Parameter coefficients for models predicting the first and second modal frequencies.

Table One suggests that the horizontal acceleration of the deck is the most influential variable affecting the first modal frequency, closely followed by the traffic loading and the vertical acceleration of the deck when winds are strong and are hitting the bridge side on. Interestingly, the lagged traffic loading variable and also the lagged temperature variable also have some significance. For the traffic loading, this most likely suggests that the model will benefit from a more sophisticated traffic loading estimate than can be provided by a single parameter, it is unlikely that the traffic on the bridge half an hour previously actually affects the modal frequencies at the time. Easier to believe is that the lagged temperature variable has some interpretable significance, as changing temperatures will induce thermal gradients which will in turn affect the stiffness of the structure.

The second mode variable coefficients show a similar pattern to those of the first modal frequency model, with vertical acceleration during times of strong winds from the North or South and horizontal acceleration at other times being the most important parameters. However, as expected from the analysis above (see Figure 6(a)), temperature plays a more dominant role in the prediction model. Traffic loading has less dominant coefficient than that for the first mode.

It is also interesting to note which variables are not influential to the modal frequency. Vertical deck acceleration has an insignificant coefficient, which is perhaps unexpected. Furthermore, introducing quadratic parameters has not had any significant affect, which is perhaps because most input variables have a linear effect (or bilinear in the case of deck acceleration), but may also be because the true nonlinearity (apart from the bilinearity mentioned, which is added explicitly by switching of the variable here) cannot be represented suitably by a quadratic form.

3.1.3 Tentative steps towards Damage Detection

For a working SHM system there must be a mechanism for detecting the occurrence of damage. Furthermore, for structures outside the laboratory, a damage indicator must be able to distinguish between changes in structural response due to environmental and operational variations, and those caused by damage. Indeed this is considered one of the largest stumbling blocks for the transferral of SHM to civil structures [14]. A considerable amount of research has already gone into this topic (see [15] for a good summary) and one idea that is very relevant to the analysis here is the suggestion of using model prediction errors as a damage indicator, where the model is trained on data from the structure in its normal condition [16]. As long as the model can predict the monitored variable(s) in question with a good degree of accuracy, any large increase in model prediction error can be taken to mean that the structure has deviated from its normal condition. If the simple models used above in an attempt to better understand the bridge's normal condition are capable of predicting the modal frequency change to a good and most importantly consistent degree, their prediction errors would be a good candidate for a damage indicator that is not affected by environmental and operational conditions.

Figure 15 plots the errors of the model described above for the first modal frequency, with confidence limits at plus and minus three standard deviations of the errors from the training period. Apart from very few anomalies, the model errors stay within the confidence interval, which demonstrates that a model of this type could be used as a potential damage detector. As always the problem lies in the fact that no damage data is available for validation of this statement. However, in this case, more data than those used for model training and validation are available from the period of time when a there was a suspected sensor fault. Figure 16 shows the model prediction errors of the same model with the additional data set added on the end. Errors clearly depart significantly from the confidence interval during the time of the suspected sensor fault. Although, this is somewhat a synthetic example, it does show that the model error plot is able to detect a departure from the normal response condition.

As the section title suggests, this is a tentative step towards the development of a system capable of damage detection. The model for the first modal frequency is a success in that it can detect a departure from the normal condition, the model parameters have also been useful for inference into the physical mechanisms behind the fluctuating modal parameters. However, there is still a long way to go as far as practical damage detection is concerned. One damage indicator based on one modal frequency would evidently not be sufficient to reliably detect damage in such a structure. Any credible system put in place for the detection of damage would need a number of such predictive models taking into account different response measurements, not just global modal parameters. Furthermore, although the detection of a sensor fault with the frequency prediction model was a useful exercise to show how a departure from the normal condition could be detected, it illustrates perfectly another challenge that must be met with before any damage indicator can be relied upon, which is that it must be able, not only to distinguish between response fluctuations caused by environmental and operational conditions but to distinguish between sensor faults and real structural damage. If model prediction errors are to be used as a damage indicator sensor faults must be detected before any data is inputted to the model. For further reading on detecting sensor faults see, for example [17].

4 Summary

The current paper has introduced and described the substantial monitoring campaign being carried out on the Tamar Suspension Bridge in the Southwest of England. Three monitoring systems currently in place have provided a wealth of data detailing the static and dynamic behaviour of the bridge deck and cables, as well as the operational and environmental factors affecting them.

The second half of the paper has addressed which environmental/operational conditions drive the fluctuations observed in the modal frequencies of the deck obtained from acceleration data by a data-driven SSI routine. Traffic loading was found to be a dominant driver of daily frequency fluctuation, whilst temperature was found to have more of a seasonal effect than daily. Lastly, the acceleration of the

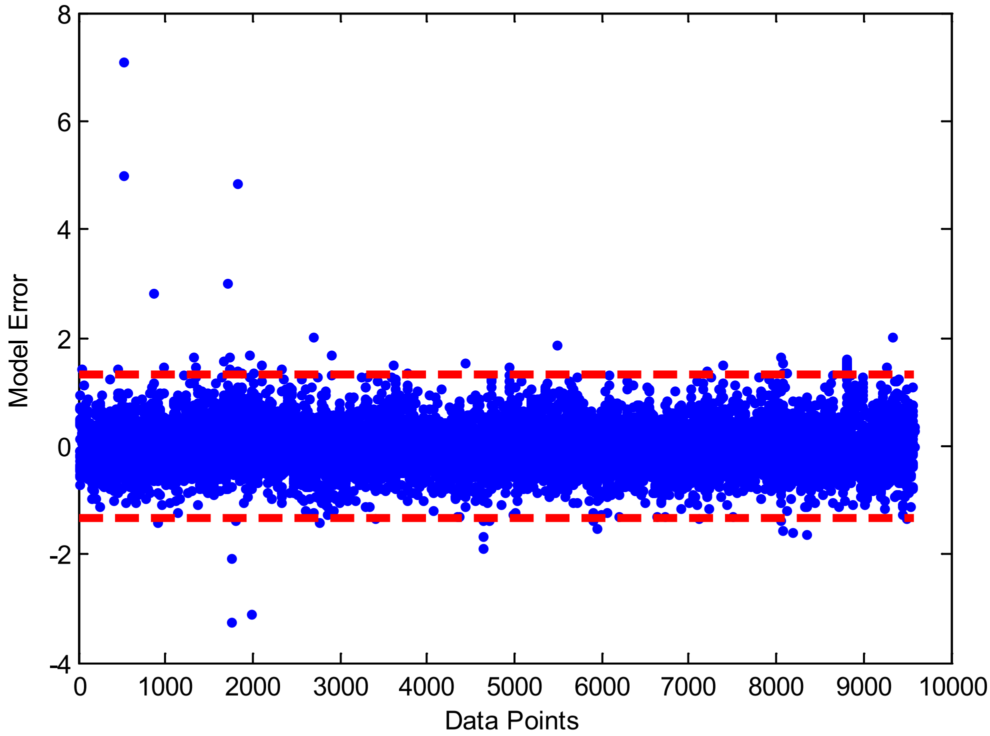


Figure 15: Model Errors of the prediction for the first modal frequency

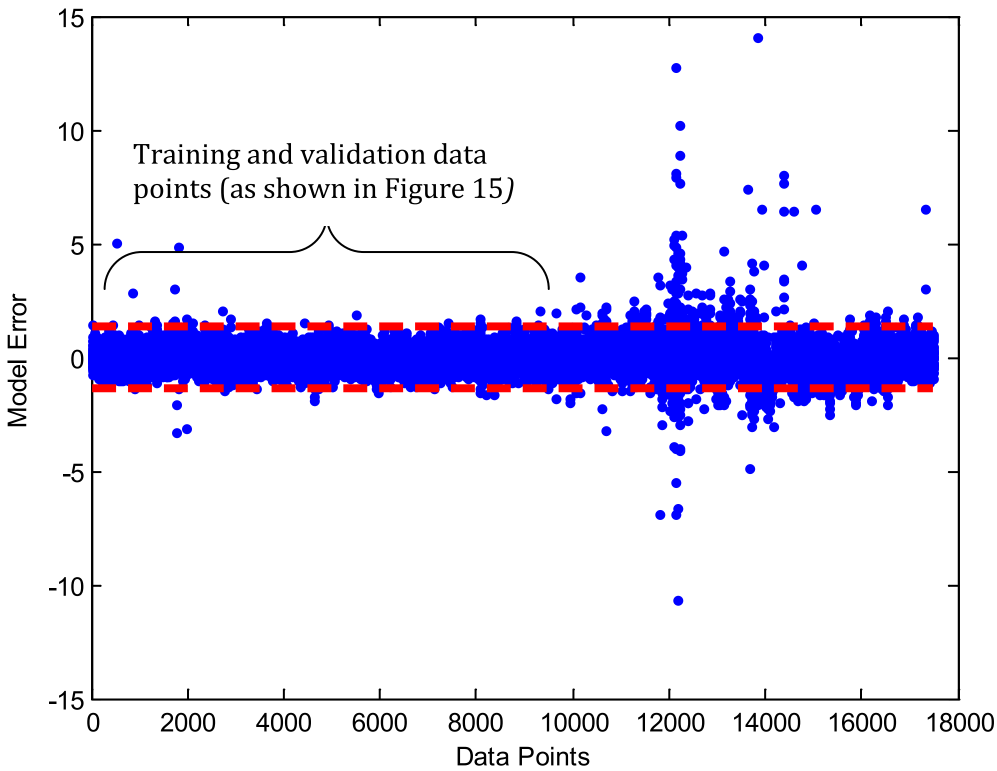


Figure 16: Model Errors of the prediction for the first modal frequency including period of suspected sensor fault

deck was found to have a significant effect on the modal frequencies at times when the wind speed was higher than 25mph and hitting the bridge side-on.

Finally, response surface models have been fitted in attempt to predict the modal frequency changes of the bridge deck given the measured environmental/operational conditions. It was found that a simple response surface model with input parameters based on the estimated traffic loading, temperature and deck acceleration (in turn dependent on the wind speed and direction) can predict the change in the first modal frequency to a good degree of accuracy. The higher modal frequencies can also be predicted with similar models, although with less accuracy. A suggestion has been made that the errors of the successful models could be incorporated into a damage detection system for the bridge.

References

1. Wenzel, H., *Health monitoring of bridges*. 2009: Wiley Online Library.
2. Peeters, B. and De Roeck, G., *Reference-based Stochastic Subspace Identification for output-only modal analysis.* Mechanical Systems and Signal Processing, 1999. **13**(6): p. 855-878.
3. Alampalli, S., *Effects of Testing, analysis, damage, and environment on modal parameters.* Mechanical Systems and Signal Processing, 2000. **14**(1): p. 63-74.
4. Cornwell, P., Farrar, C., Doebling, S., and Sohn, H., *Environmental variability of modal properties.* Experimental Techniques, 1999. **23**(6): p. 45-48.
5. Peeters, B., Maeck, J., and Roeck, G., *Vibration-based damage detection in civil engineering: excitation sources and temperature effects.* Smart Materials and Structures, 2001. **10**: p. 518.
6. Siringoringo, D. and Fujino, Y., *System identification of suspension bridge from ambient vibration response.* Engineering Structures, 2008. **30**(2): p. 462-477.
7. Kim, C., Jung, D., Kim, N., Kwon, S., and Feng, M., *Effect of vehicle weight on natural frequencies of bridges measured from traffic-induced vibration.* Earthquake Engineering and Engineering Vibration, 2003. **2**(1): p. 109-115.
8. Transport Statistics Bulletin, *Road Statistics 2007.* 2007.D.f.T. UK.
9. Sharma, S., *Applied multivariate techniques*. 1995, New York, USA.: John Wiley & Sons, Inc.
10. Box, G. and Draper, N., *Empirical model-building and response surface*. 1986, New York, USA.: John Wiley & Sons, Inc.
11. Box, G. and Wilson, K., *On the experimental attainment of optimum conditions.* Journal of the Royal Statistical Society. Series B (Methodological), 1951. **13**(1): p. 1-45.
12. Ni, Y., Hua, X., Fan, K., and Ko, J., *Correlating modal properties with temperature using long-term monitoring data and support vector machine technique.* Engineering Structures, 2005. **27**(12): p. 1762-1773.
13. Ni, Y.Q., Zhou, H.F., and Ko, J.M., *Generalization capability of neural network models for temperature- frequency correlation using monitoring data.* Journal of Structural Engineering, 2009. **135**(10): p. 1290-1300.
14. Farrar, C.R. and Worden, K., *An introduction to structural health monitoring.* Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 2007. **365**(1851): p. 303-315.
15. Sohn, H., *Effects of environmental and operational variability on structural health monitoring.* Philosophical Transactions of the Royal Society A: Mathematical Physical and Engineering Sciences, 2007. **365**(1851): p. 539-560.
16. Peeters, B. and De Roeck, G., *One-year monitoring of the Z24-Bridge: environmental effects versus damage events.* Earthquake Engineering & Structural Dynamics, 2001. **30**(2): p. 149-171.
17. Kullaa, J., *Sensor validation using minimum mean square error estimation.* Mechanical Systems and Signal Processing, 2010. **24**(5): p. 1444-1457.